Exploring The Impact Of AI-Related Motivation on Self-Regulated Learning Among University Student in Samarinda

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ABSTRACT

The rapid advancement of artificial intelligence (AI) technology has transformed the landscape of higher education, prompting students to integrate AI into academic activities. This study examines the influence of AI use motivation on students' self-regulated learning (SRL) among university students in Samarinda, Indonesia, a developing urban context that remains underrepresented in empirical research on AI-enhanced learning. Employing a quantitative approach and causal associative design, data were collected from 384 active university students who had prior experience using AI tools. The instruments used were the QAIUM scale and SRL scale, both of which were validated for reliability and construct accuracy. Results from simple linear regression analysis revealed a significant negative effect of AI use motivation on SRL, with a contribution of 10.8%. These findings indicate that higher motivation to use AI may be associated with reduced capacity for independent planning, monitoring, and evaluation of learning processes, suggesting a potential risk of digital dependency. From a practical perspective, the results highlight the need for educational practices and policies that promote balanced and reflective AI use, emphasizing the development of students' self-regulatory skills alongside technological integration. This study contributes theoretically by integrating the Expectancy-Value framework with Zimmerman's SRL model and provides context-specific empirical evidence to inform AI-related educational strategies in similar emerging higher education settings.

Keywords : AI use, artificial intelligence, motivation, self-regulated learning, university student

Introduction

The rapid development of information and communication technology has significantly reshaped daily life, including the realm of education. Society now coexists with advanced technologies such as gadgets and artificial intelligence (AI), which facilitate access to information, task completion, and learning support (Hutabarat, Ompusunggu, Silaban, Padang & Nababan, 2022; Rahmadina & Marsofiyati, 2024). Gadgets, as online media, positively encourage students to expand their knowledge (Herlambang, 2020), while AI emerges as a technology capable of mimicking human intelligence in problem-solving, understanding learning processes, and making decisions (Gitakarma & Tjahyanti, 2022; Saifullah et al, 2024)

AI now plays a pivotal role in higher education—not merely as a tool, but as a transformative agent in learning processes. It enables rapid information access, adaptive content delivery, and automated guidance (Salsabila, Kustati, Gusmirawati & Amelia, 2024; Sugiarto, Sulindra & Adnan, 2024). AI use has also been shown to enhance students' intrinsic motivation through adaptive and interactive features such as chatbots and virtual tutors (Abdurrahman, Rizki & Pradana, 2025) aligning with Deci & Ryan (1985) motivation theory, which emphasizes the importance of intrinsic motivation in sustaining academic engagement (Deci & Ryan, 1985).

According to the Indonesian Dictionary (Kamus Besar Bahasa Indonesia [KBBI], 2021), motivation refers to an internal drive, either conscious or unconscious, that compels individuals to act toward specific goals. Abraham Maslow defines motivation as a persistent, dynamic, and complex force inherent in all organismic activity (Prawira, 2016). It is an energetic impulse or personal condition that drives individuals to act, involving changes in emotion and reaction in pursuit of specific objectives.

Drawing on Expectancy-Value Theory (Wigfield & Eccles, 2000; Yurt & Kasarci, 2024), motivation is shaped by individuals' expectations of learning outcomes and the perceived value of AI use. This framework includes five dimensions: expectancy, attainment value, utility value, intrinsic/interest value, and cost (Yurt & Kasarci, 2024) While several studies suggest that AI can enhance student engagement and interest in learning (Muchminiin, Rahmadhani, Muqorobin, Mustaghfirullah & Luthfi, 2024; Rosiana, Cahyanti, Rahayu, 2023), excessive reliance on AI has also been linked to diminished critical thinking skills (Adhadi et al, 2024; Lukman, Agustina & Aisy, 2024).

Conversely, self-regulated learning (SRL) is a crucial capability that enables students to independently manage, monitor, and evaluate their learning processes (Schraw, Kauffman & Lehman, 2006; Zimmerman, 1990). Students are considered self-regulated learners to the extent that they engage metacognitively, motivationally, and behaviorally in their own learning (Zimmerman, 1986; Zimmerman 1989). This process comprises three phases: forethought (planning and goal setting), performance (monitoring and learning strategies), and self-reflection (evaluation and response to outcomes) (Zimmerman, 2000). Based on Bandura, SRL is influenced by personal, behavioral, and environmental factors (Zimmerman, 1986), and prior research indicates that SRL can be enhanced through educational technologies, including digital platforms and applications Ana, & Achdiani, 2015; Meilani, Cakrawati & Sugiarti, 2017).

In this context, AI can support students in developing SRL by offering tools that assist with academic tasks, such as real-time feedback and personalized learning analytics. Effective SRL enables students to improve academic performance, maintain achievement, and balance their roles as learners (Andryani, Aspin, & Silondae, 2022)

However, studies directly examining the relationship between AI use motivation and SRL remain limited, with most focusing on either variable independently. This study addresses that gap by investigating the influence of AI use motivation on SRL among university students in Samarinda.

The researchers argue that motivation to use AI is not solely about technological adaptation but also about its potential contribution to fostering independent learning. By integrating the Expectancy-Value framework with Zimmerman's SRL model, this study aims to offer new insights into adaptive, technology-based learning strategies.

The objective of this research is to explore the extent to which AI use motivation affects students' SRL capabilities in Samarinda. The study seeks to contribute both theoretically to the academic literature and practically to the development of learning strategies that promote autonomy in the digital age.

Methods

A. Participant characteristics and research design

This study employed a quantitative approach with a causal associative design aimed at examining the cause-and-effect relationship between AI use motivation and self-regulated learning (SRL) (Sugiyono, 2016). The research was conducted among active university students in Samarinda, encompassing both male and female participants from various higher education institutions who had prior experience using AI technologies.

B. Sampling procedures

A non-probability purposive sampling technique was applied, selecting participants based on specific criteria: active enrollment in a Samarinda-based university and prior use of AI technology. Data collection was conducted both in-person at several institutions Universitas Muhammadiyah Kalimantan Timur, Universitas Mulawarman, and dan Politeknik Kesehatan Kemenkes Kalimantan Timur, and online via WhatsApp and Instagram using Google Forms.

C. Sample size, power, and precision

The population consisted of all university students in Samarinda, totaling 72,046 individuals based on data from Badan Pusat Statistik (BPS) KalimantanTimur in 2025. A sample of 384 respondents was determined using the Isaac and Michael sampling table with a 5% margin of error (Sugiyono, 2016).

D. Measures and covariates

Two instruments were used: the AI Use Motivation Scale and the SRL Scale. The AI motivation scale was based on the Questionnaire of AI Use Motives (QAIUM) developed by Yurt & Kasarci (Yurt & Kasarci, 2024), grounded in Expectancy-Value Theory (Wigfield & Eccles, 2000), comprising five dimensions: expectancy, attainment value, utility value, interest/intrinsic value, and cost. The instrument was officially translated into Bahasa Indonesia by a certified translator. The SRL scale was constructed based on Zimmerman's (1989) model, encompassing metacognitive, motivational, and behavioral aspects. Cronbach's alpha reliability coefficients were 0.871 for QAIUM and 0.845 for SRL, indicating strong internal consistency for both instruments. The following table summarizes the QAIUM item distribution:

Table 1. QAIUM Scale Blueprint

Dimension	Item Numbers	Number of Items
Expectancy	1, 2, 3	3
Attainment Value	4, 5, 6, 7	4
Utility Value	8, 9, 10, 11	4
Instrinsic/Interest Value	12, 13, 14, 15	4
Cost	16, 17	2

Table 2. SRL Scale Blueprint

Aspect	Indicator	Item Numbers		Number of Items
		F	UF	
Metacognitive	Learning strategy planning	1, 10	-	2
	Comprehension monitoring	16, 20	-	2
	Learning outcome evaluation	2, 24	17	3
Motivational	Self-management strategies	11, 18, 25	-	3
	Goal setting	27, 28	3, 7, 12	5
	Persistence	8, 13	21	3
Behavioral	Self-observation	22	4, 9	3
	Self-evaluation	19	14	3
	Self-reaction	15, 23, 26	6	4

E. Measures and covariates

Data analysis was conducted using SPSS Statistics version 27 for Windows. Prior to hypothesis testing, descriptive statistics were calculated to examine the distribution, central tendency, and variability of the data. Assumption testing was performed to ensure the suitability of regression analysis, including normality testing using the Kolmogorov–Smirnov test and linearity testing through analysis of variance (ANOVA) for deviation from linearity.

Hypothesis testing was carried out using simple linear regression analysis, as the study aimed to examine the direct effect of a single independent variable, AI use motivation, on the dependent variable, self-regulated learning (SRL). AI use motivation was specified as the predictor variable based on Expectancy–Value Theory, while SRL was positioned as the outcome variable following Zimmerman's self-regulated learning framework.

The regression model was evaluated using the F-test to determine overall model significance, while the regression coefficient (β) was used to assess the direction and magnitude of the relationship between variables. Statistical significance was determined using a significance level of $p < 0.05$. Effect size was assessed using the coefficient of determination (R^2), which represents the proportion of variance in SRL explained by AI use motivation.

Results Of Study

This study analyzed data from 384 eligible respondents, whose demographic characteristics were categorized into six aspects: age, gender, institution, educational level, frequency of AI use, and types of AI applications utilized. These classifications were intended to map respondent profiles and support targeted data analysis.

Tabel 3. Age Distribution

Age	Frequency (N)	Percentage (%)
18	10	2,6%
19	25	6,5%
20	40	10,4%
21	96	25,0%

22	117	30,5%
23	59	15,4%
24	15	3,9%
25	13	3,4%
26	2	0,5%
27	3	0,8%
28	2	0,5%
29	1	0,3%
32	1	0,3%

The majority of respondents were aged 21 (n = 96, 25.0%) and 22 (n = 117, 30.5%), indicating that most participants were in early adulthood. Other age groups ranged from 18 to 32 years, with smaller proportions.

Tabel 4. Gender Distribution

Gender	Frequency (N)	Percentage
Male	155	40%
Female	229	60%

Female students comprised 60% of the sample (n = 229), while male students accounted for 40% (n = 155), indicating a higher level of participation among women in this study.

Tbel 5. Level Of Education

Level of Education	Frequency (N)	Percentage (%)
S1	294	77%
S2	15	4%
S3	0	0%
D3	44	11%
D4	25	7%
Professional Education	6	2%

Most participants were enrolled in undergraduate programs (S1, 77%), followed by diploma (D3, 11%), applied bachelor (D4, 7%), master's (S2, 4%), and professional education (2%). No doctoral students (S3) were included.

Tabel 6. Frequency of AI Use

Usage Frequency	Frequency (N)	Percentage (%)
≥7 times per week	173	45%
5-6 times per week	124	32%
<5 times per week	42	11%
Rarely (<2 times per week)	45	12%
Never	0	0%
Total	384	100%

A substantial portion of respondents reported using AI ≥7 times per week (n = 173, 45%) or 5–6 times per week (n = 124, 32%). Only 12% used AI less than twice weekly, and none reported never using AI.

Tabel 7. Types of AI Applications

AI Application	Frequency (N)	Percentage (%)
Blackbox.AI	5	1,30%
Canva	201	52,34%
Character AI	1	0,26%
ChatGPT	352	91,67%
Claude	45	11,72%
Copilot	43	11,20%
DeepSeek	5	1,30%
Elicit	1	0,26%
Gemini	157	40,89%
Grok	3	0,78%
Perplexity	163	42,45%
Poe	1	0,26%
Scite.ai	1	0,26%
Typeset	1	0,26%

ChatGPT was the most frequently used AI tool (n = 352, 91.67%), followed by Canva (n = 201, 52.34%), Perplexity (n = 163, 42.45%), and Gemini (n = 157, 40.89%). Other tools such as Claude and Copilot were also used, though less frequently.

Descriptive statistical analysis in this study was conducted using SPSS Statistics version 27 for Windows. The analysis aimed to provide an overview of the distribution and tendencies of scores across the two main research variables: AI use motivation and self-regulated learning (SRL).

Tabel 8. Descriptive Statistic for Both Variables

Variable	Min	Max	Mean	SD
AI Use Motivation	34	68	55.25	6.345
Self-Reglated Learning	62	112	86.16	9.291

The results indicate that the AI use motivation scores among the 384 respondents ranged from 34 to 68, with a mean of 55.25 and a standard deviation of 6.345. Meanwhile, SRL scores ranged from 62 to 112, with a mean of 86.16 and a standard deviation of 9.291. These findings provide a general depiction of the distribution and central tendency of both variables, suggesting moderate levels of AI use motivation and SRL among the participants.

A. Descriptive statistics

To further interpret the data, both variables were categorized into three levels, low, moderate, and high, based on interval calculations conducted using Microsoft Excel. The categorization results are presented in the following tables.

Tabel 9. Categorization of AI Use Motivation

Category	Interval	Frequency (N)	Percentage (%)
Low	X < 49	58	15%

Moderate	49 ≤ X < 62	282	73%
High	X > 62	44	11%

The categorization of AI use motivation reveals that the majority of respondents (73%) fall within the moderate category, followed by 15% in the low category and 11% in the high category. This suggests that most students possess a reasonably strong internal drive to utilize AI in support of their academic activities.

Tabel 10. Categorization of SRL

Category	Interval	Frequency (N)	Percentage (%)
Low	X < 77	66	17%
Moderate	77 ≤ X < 95	245	64%
High	X > 95	73	19%

The SRL categorization indicates that most respondents (64%) demonstrate moderate levels of self-regulated learning, with 17% categorized as low and 19% as high. These results reflect a relatively stable capacity for independent learning among the participants, although there remains room for improvement in reflective and metacognitive aspects.

B. Normality and Linearity Test

To ensure the validity of the regression analysis, assumption testing was conducted using SPSS Statistics version 27 for Windows. The normality of the data was assessed using the Kolmogorov-Smirnov test, while linearity was evaluated to determine the nature of the relationship between the independent and dependent variables.

Tabel 11. Normality test result

Variable	Asymp. Sig. (2-tailed)	Interpretation
AI Use Motivation and SRL	.076	Normally Distributed

The Kolmogorov-Smirnov test yielded a significance value of 0.076, which exceeds the threshold of 0.05. According to the decision criteria for normality testing, this result indicates that the data are normally distributed. Therefore, the assumption of normality required for regression analysis is satisfied.

The linearity test in this study was conducted using SPSS Statistics version 27 for Windows, with decision-making based on the significance value (Sig.). A statistically significant linear relationship between the independent and dependent variables is indicated when the Sig. value for *Deviation from Linearity* is greater than 0.05. Conversely, a value below 0.05 suggests that no significant linear relationship exists between the two variables.

Tabel 12. Linearity Test Result

Variable	Sig. Deviation from Linearity	Interpretation
AI Use Motivation and SRL	.196	Linear Relationship

Based on the results of the linearity test, the Sig. value obtained was 0.196, which is greater than 0.05. This indicates a statistically significant linear relationship between AI use motivation and self-regulated learning (SRL), thus confirming that the data meet the assumption of linearity.

C. Hypothesis testing and regression result

Hypothesis testing in this study was conducted through a simple linear regression analysis using SPSS Statistics version 27 for Windows. The decision criterion was based on the comparison between the significance value (Sig.) and the probability threshold of 0.05. A Sig. value less than 0.05 indicates a statistically significant effect of AI use motivation on self-regulated learning (SRL), whereas a value greater than 0.05 suggests no significant effect. The magnitude of the effect was assessed using the R Square value, which reflects the proportion of variance in the dependent variable explained by the independent variable.

Tabel 13. Simple linear regression result

Variable	F	Sig.	Regression Coefficient	R^2
AI Use Motivation and SRL	46.272	.001	-.406	.108

The results of the simple linear regression analysis indicated that the regression model was statistically significant ($F = 46.272$, $p < 0.001$), confirming that AI use motivation significantly predicts self-regulated learning. The negative regression coefficient ($\beta = -0.406$) indicates an inverse relationship between the two variables, whereby higher levels of AI use motivation are associated with lower levels of SRL.

The coefficient of determination ($R^2 = 0.108$) suggests that AI use motivation accounts for 10.8% of the variance in self-regulated learning. Although the effect size is modest, it indicates a meaningful contribution within behavioral and educational research, where learning outcomes are influenced by multiple interacting factors. The remaining variance in SRL may be explained by other cognitive, motivational, or contextual variables not examined in this study.

Discussion

The results of the simple linear regression analysis indicate that AI use motivation has a significant negative effect on students' self-regulated learning (SRL) in Samarinda. The regression model was statistically significant ($F = 46.272$, $p = 0.001$), suggesting that the model adequately explains the relationship between the variables. The regression coefficient of -0.406 implies that the higher the students' motivation to use AI, the lower their level of SRL. This suggests that excessive reliance on AI may potentially weaken students' capacity to independently manage and regulate their learning processes.

This finding is supported argue that intensive adoption of AI technology can lead to digital dependency, thereby diminishing students' metacognitive and reflective skills (Lan & Zhou, 2025). Digital dependency, refers to a condition in which students excessively rely on technology, specifically AI, to support or even replace self-directed learning processes that should be internally regulated (Lan & Zhou, 2025). Similarly, notes that personalized AI systems often shift the responsibility for learning from students to the system itself, which may disrupt the development of SRL, particularly in the planning and self-evaluation phases (Babayev, 2025).

The contribution of AI use motivation to SRL was relatively modest, with an R^2 value of 0.108, indicating that only 10.8% of the variance in SRL is explained by AI use motivation. This suggests that SRL is influenced by a broader set of factors not captured in this study. The Expectancy-Value Theory by Wigfield dan Eccles offers a useful framework for interpreting this result (Wigfield, & Eccles, 2000). According to the theory, learning motivation is shaped by students' expectancy for success and the value they assign to the task. In this context, students may be motivated to use AI due to its practical benefits (utility value) and personal interest (interest value), although they may not yet perceive AI as integral to their academic identity (attainment value), and may still weigh the costs, such as time, effort, and risk of failure, associated with active AI use.

Demographic data show that the majority of respondents were 22 years old and enrolled in undergraduate programs at universities. This age falls within early adulthood, a developmental stage characterized by increasing responsibilities, self-acceptance, and potential development (Sari, 2021). University environments typically encourage independent learning and exploration of digital resources, including AI, which may influence students' motivation and frequency of AI use. Most respondents reported using AI tools regularly, between 5 to 7 times per week, with platforms ranging from ChatGPT, Gemini, and Perplexity to Canva. The high usage frequency suggests that AI has become a central component in supporting academic activities, particularly in reference management and strategic learning. However, from another perspective, who emphasize the importance of digital literacy and ethical awareness in AI use to prevent declines in intrinsic motivation and critical thinking (Zulfikhar, Murthada, Nuffaiz, Majid, & Sumarno, 2024).

The past research found that only students with high AI literacy are able to integrate technology effectively into SRL (Shi, Liu, & Hu, 2025); otherwise, AI tends to reinforce passive learning behaviors, similarly observed that AI positively impacts SRL only when accompanied by explicit metacognitive support, such as automated reflection features or feedback-based AI tutors (Zimmerman, 1986). Another finding noted that AI use in learning can create engaging and innovative experiences, enhancing student satisfaction and interest (Hapsari, Ramadhani, & Ikramullah, 2024). further support this view, showing that AI use significantly boosts learning motivation when supported by adequate digital literacy and responsive learning environments. Thus, students' motivation to use AI stems not only from accessibility or technological trends but also from their perception of its functional and emotional value.

Students are considered to exhibit SRL when they actively manage their learning through metacognitive strategies, motivation, and autonomous behavior, without direct guidance from others. Another emphasize that internal drive is the foundation of directed learning (Aisyah & Alfita, 2017). Santrock (Aisyah & Alfita, 2017) defines SRL as the ability to generate and monitor one's thoughts, feelings, and behaviors to achieve learning goals. In this context, motivation to use technology serves as a driving factor that activates regulatory mechanisms in learning. AI functions not only as a tool but also as a catalyst for more intentional learning awareness.

Categorization data show that most students (73%) fall into the moderate category of AI use motivation. This indicates that the study does not merely examine AI usage, but rather the internal drive to integrate AI meaningfully into learning processes. This aligns found that expectancy and value dimensions in the QAIUM are strongly influenced by individual perceptions of AI's benefits and challenges (Yurt & Kasarci, 2024). The dominance of the moderate category may reflect a transitional phase, where students are beginning to explore AI's advantages but have not yet fully integrated it as a personal and strategic learning tool.

Additionally, 245 out of 384 respondents (64%) were categorized as having moderate SRL ability. This suggests that while most students are beginning to learn independently, they are not yet consistent in reflecting and evaluating their learning outcomes. Their self-regulation is developing but not yet optimal. Conceptualizes SRL as a process involving reciprocal interactions among personal, behavioral, and environmental factors (Zimmerman, 1986). His model outlines three phases: forethought (planning and goal-setting), performance (monitoring and strategy use), and self-reflection (evaluation and reaction) (Zimmerman, 2000). AI use motivation plays a key role in the forethought phase, where students are driven to set and design learning strategies. AI also supports the performance phase through features that enable monitoring and feedback, and enhances self-reflection by providing data and insights that help students evaluate their learning processes.

The moderate category indicates that most students have likely engaged in the initial stages of self-regulated learning (SRL), such as setting learning goals and planning strategies, yet have not fully optimized the evaluation of their learning outcomes. This observation is consistent with the findingswho reported that students with moderate SRL levels tend to experience a state of flow during online learning, a condition characterized by intense focus, intrinsic motivation, and a distorted sense of time, while still lacking in-depth self-evaluation practices (Kriswanti & Mastuti, 2021). Motivation to use artificial intelligence (AI) may contribute to the forethought phase, in which motivated students are more likely to define and select clearer learning objectives. Furthermore, AI technologies can support the performance phase by offering features that facilitate monitoring and feedback, and strengthen the self-reflection phase by providing data and insights that assist students in evaluating their learning processes more effectively.

Statistical analysis shows that the average score for AI use motivation was relatively high, indicating that students are actively motivated to use AI in their academic activities and are capable of managing their learning independently. According to the Expectancy-Value Theory, this stable and relatively high motivation reflects students' positive expectations of their ability to use AI and their perception of its usefulness in achieving academic goals. This aligns with the concepts of utility value and interest value, where students not only see AI as a technical aid but also enjoy using it. Meanwhile, the SRL findings support Zimmerman's three-phase model, showing that students are beginning to plan and monitor their learning, although their reflection remains suboptimal.

This study offers empirical contributions by integrating the Expectancy-Value approach with Self-Regulated Learning theory in the context of local university students in Samarinda. The use of the Indonesian-translated version of the QAIUM instrument represents an innovative adaptation that has not been widely applied in similar studies in Indonesia. Although the findings indicate a significant relationship, the contribution of AI use motivation to SRL remains modest at 10.8%, suggesting the presence of other external factors not explored in this study. Moreover, the sample was dominated by students who use AI in general, rather than strategically and systematically in their daily learning activities.

In addition to its theoretical contribution, these findings carry important practical implications for higher education learning practices. The observed negative relationship between AI use motivation and self-regulated learning suggests that AI integration should be accompanied by pedagogical strategies that actively foster students' metacognitive awareness and reflective thinking. Without such guidance, high motivation to use AI may increase the risk of digital dependency, potentially undermining students' ability to independently plan, monitor, and evaluate their learning. Therefore, practical recommendations for balancing AI use and self-regulated learning are further elaborated in the conclusion section.

Conclusions And Recommendation

This study concludes that AI use motivation has a significant negative effect on students' self-regulated learning (SRL), accounting for 10.8% of the variance. Although university students in Samarinda demonstrate relatively high motivation to use AI for academic purposes, such motivation does not necessarily translate into stronger learning autonomy. Instead, excessive reliance on AI may reduce students' reflective, metacognitive, and evaluative learning processes, which are central components of SRL.

These findings highlight important implications for educational practice. Rather than positioning AI solely as a tool for efficiency or task completion, AI should be intentionally integrated as a cognitive and metacognitive support system that encourages students to actively plan, monitor, and reflect on their learning. For example, AI tools can be used to generate reflective prompts, support goal-setting activities, or provide feedback that requires students to evaluate and revise their learning strategies, rather than supplying direct answers.

To mitigate the risks of digital dependency, higher education institutions are encouraged to provide structured guidance on responsible and reflective AI use. Practical strategies may include workshops on AI literacy and self-regulated learning, instructional designs that integrate AI-assisted learning with reflective assignments, and pedagogical guidelines that emphasize AI as a learning scaffold rather than a substitute for independent thinking.

Future research is recommended to examine additional factors influencing self-regulated learning in AI-enhanced environments, such as AI literacy, self-efficacy, and instructional design features. Longitudinal and experimental studies may further clarify how balanced AI integration can support sustainable self-regulated learning practices across diverse educational contexts.

Acknowledgment

Gratitude is expressed to all respondents for their participation and contributions, as well as to the Department of Psychology at Universitas Muhammadiyah Kalimantan Timur for the academic support and research facilities provided. The author further acknowledges the support of family and close colleagues whose encouragement was instrumental during the research process.

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